Development of Machine Learning Enabled Chatbot for Promoting Eating Habits Changes

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Abstract*. Unhealthy eating habits are one of the most important health problems in the world and are addressed in various ways, including digital technologies. The aim of this research is to develop a chatbot that allows tracking food consumption and monitoring the dynamics of nutrient intake in a non-intrusive way. For this purpose, we used a design science research approach. The chatbot uses multiple machine learning models (ML) with semantic similarity algorithms and enables human feedback to improve its performance. We developed it using the Serverless framework and deployed it on the Amazon Web Services (AWS) platform. Our goal is to create an innovative and user-friendly method for tracking food consumption and nutrient dynamics to promote healthier eating habits.*

Keywords. Healthy eating, grocery store receipt, nutritional analysis, daily intake monitoring, machine learning, chatbot

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1 Introduction

This research aims to address the problem of promoting healthy eating habits by developing a user-friendly chatbot using a string of machine learning models. Unhealthy eating habits are among most important risk factors for cardiovascular diseases (CVD), which are the leading cause of death worldwide, claiming an estimated 17.9 million lives each year [1]. We derive our thesis from the idea that changing the user's eating habits can be stimulated by providing feedback information using non-intrusive digital technology. While the market for health-tracking applications is saturated, with Google Play listing over a hundred apps when searching for “calorie counter” [2], most of these apps rely on recording every meal as the primary method for tracking food consumption. This approach demands willpower and discipline from users, requiring them to log their meals 4-5 times a day. In contrast, our aim is to support the users (individual or household) to change their habits by providing a long-term feedback on the grocery purchases by scanning their receipts from grocery stores or restaurants. The limitation of the proposed approach is in calorie calculation accuracy, as it cannot track unpaid non-receipt meals (food purchased but not eaten; food purchased but eaten by others; food eaten in an environment where there was no receipt, such as at a picnic). Thus, we propose the following research question, "How can we use open source ML models and ML services in order to make consumption tracking more user friendly?".

The use of digital technologies in healthcare and well-being has increased dramatically in recent decades. An important body of research focused on healthier lifestyles, behaviour change, and healthier food consumption has approached this problem with different ideas and methods. Some of them focused on the point-of-sale nutrition scoring systems and nutrition-information applications to guide consumers towards healthier food choices [3], [4]. Others focused to providing insights into the quality of nutrition content (using mobile apps) and the influence of external factors like in-store marketing on consumers' decisions [5]–[8] further demonstrated that monitoring eating behaviour and consistent health behaviour tracking can lead to healthier habits and significant long-term weight loss. Vu et al. [9] examined the complexity of automatic diet monitoring, leading to a focus on semi-automatic methods. Pioneering studies by Ransley et al.[10] and Martin et al.[11] on non-intrusive methods for estimating food consumption by analysing grocery receipts found a strong correlation between the share of product rich in fat purchased and being overweight or lean. Current research takes one step further to enable the tracking of purchase dynamics. Appelhans et al. [12] investigated the relationship between socioeconomic indicators and the energy cost and nutritional content of supermarket food purchases. Their research introduces valuable metrics that can be utilized by our chatbot for user engagement through gamification, thereby influencing food-purchasing patterns across various populations.

2 Research methodology

General approach used in this research is the design science research (DSR) [13], in which the real-life problem is solved (relevance cycle) on the basis of existing knowledge (rigor cycle) by developing an IT artefact (design cycle), which in this case is the chatbot based on several interconnected ML models and services (Figure 1). In the design cycle we follow the Cross-industry standard process for data mining (CRISP-DM)[14].

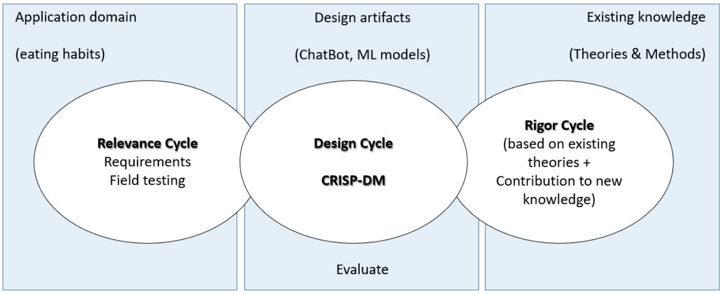

Figure 1. General design science research cycles (adapted from [13])

In the course of artefact development, the following data collection and analysis methods have been used:

- collecting grocery store receipts (from the author's family and friends),
- utilizing AWS Textract to recognize text and bounding boxes in receipt images,
- manual labelling of the text within these boxes,
- accessing open nutritional data from publicly available databases [15],[16] and
- employing semantic similarity search algorithms to map receipt entries to the database.

3 Results

Figure 2 presents the architecture of chatbot consisting of three ML-enabled components: AWS Textract for receipt optical recognition, AWS Sagemaker for fine-tuned model for labelling of bounding boxes, AWS Sagemaker built-in algorithms for mapping the product name against product database. The final evaluation is done by human experts based on 20 receipts, which haven't been used during the development.

The employed approach integrates proprietary services and open-source solutions:

- AWS Lambda (proprietary)
- AWS Sagemaker (proprietary)
- Amazon API Gateway (proprietary)
- Telegram (proprietary)
- LayoutLMv3 (open source)
- Serverless framework (open source)
- AWS Textract (proprietary)
- BlazingText (proprietary).

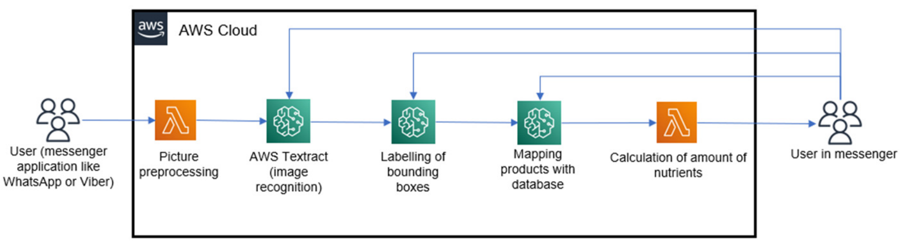

Figure 2. Chatbot architecture

The shift from a purely open-source architecture was driven by the need for enhanced development bandwidth for the researchers. While all the proprietary tools listed above have open-source counterparts, transitioning to an exclusively open-source framework would have demanded considerably more time.

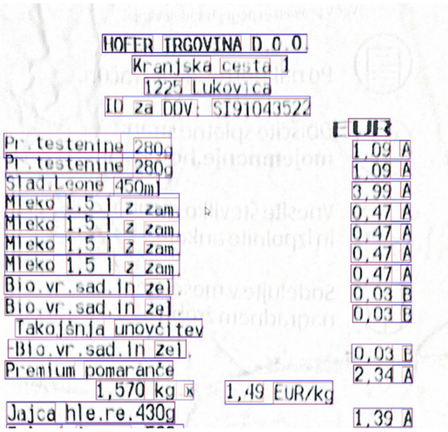

Figure 3. Part of the receipt with bounding boxes

Extraction and Recognition of Receipt Text

Paper receipts (data sources) are processed using AWS Textract, which replaced the initially tried Tesseract library due to superior results. Receipt images are stored in an AWS S3 bucket, categorized by user IDs and timestamps. When a user uploads a receipt image via Telegram, it is saved in the S3 bucket, processed by Textract, and the results are stored as {user_id}/{timestamp}/bounding_boxes.json.

Bounding Box Labelling

Receipt images undergo text and bounding box recognition using AWS Textract (Figure 3). The text within these boxes is then manually labelled with the open-source ML model, LayoutLMv3, on AWS Sagemaker. An annotation tool was developed for manual labelling, enriching the model's training data. The labelled data, which includes product names, quantities, and prices, aids in user spending analysis.

Product Name Mapping and Analysis

We access open nutritional data from public databases [16]–[21]. A semantic similarity search algorithm maps receipt entries to database records. However, the accuracy of this crowdsourced data isn't always guaranteed. The app uses AWS Sagemaker's "BlazingText" to map recognized product names to the database. It then calculates the total nutritional value of products on the receipt by multiplying quantities with nutritional data.

4 Conclusions

We addressed the problem of promoting healthy eating habits by designing a chatbot for receipt analysis. For this purpose, we used several ML models and services following the principles of the CRISP-DM process. The models and services were linked together and deployed as a web service. The developed chatbot uses AWS serverless architectures for optimal performance, the database is user-augmented for accuracy and ensures data security through encryption and anonymization. Integrated with Telegram, the chatbot offers a more streamlined consumption tracking compared to the "record every meal" method. Answering the research question, the chatbot supports a user-friendly experience by combining resource efficiency, user engagement, and robust data security. In the future we aim to test an alternative approach, by passing raw text output from OCR technology directly to a fine-tuned large language model (LLM), such as GPT-3.5. Fine-tuning GPT-3.5 [17] to recognize and interpret receipt information might enable it to handle both text extraction and semantic similarity tasks simultaneously. Despite the potential benefits, trade-offs in accuracy and computational resources required for training and deploying GPT-3.5 must be carefully assessed and compared with the current multi-modal approach. Furthermore, we aim to test the user acceptance in the field and develop a sustainable business model.

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